Who Gets Placed Where and Why?
An Empirical Framework for Foster Care Placement

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Motivation

Foster care

System that provides **temporary care** for children removed from home by child-protective services

In the U.S.

- **5.91% (1 out of 17)** of children are placed in foster care
- Every year, more than **half a million children** go through foster care
- On any given day, nearly **450,000** children are in foster care
- On average, children stay **19 months** in foster care (median = 14 months)
- Exit foster care: **reunification** (55%), **adoption** (35%), **emancipation** (10%)

Why market design in foster care?

- **Broad goal:** Study **how** matching is done, and how to **improve** it

Problem

Many foster children go through several foster homes before exiting foster care

- **Prevalent problem:** 56.1% > 1, avg $= 2.56$ (U.S., 2015)
- Evidence suggests **placement disruptions are detrimental for children**:
  - ↑ emergency and mental-health services, ↑ behavioral and attachment problems
  - affect children's bodily capacity to regulate cortisol (stress hormone)
  - More and longer placements ⇒ **as adults**: ↑ depression, smoking, drug use, criminal convictions
- Social workers (say they) try to **minimize disruptions**
  - Do what is best for children, and minimize workload

What I do

1. Recover social workers **preferences over placement outcomes**: how they weigh **duration** and **disruptions** when assigning children to foster homes
    - **Revealed preference** exercise (no explicit systematic matching algorithm)
    - Formulate and estimate **structural model of matching in foster care**

2. Use model estimates to study **new policies aimed at improving outcomes**
    - Keep **estimated preferences fixed**
    - Improve placement outcomes by **increasing market thickness** through:
        - **Geographical centralization** (centralizing regional offices)
        - **Temporal aggregation** (delaying assignments)

Why structural model?

- **Main Challenge**
  - **Objective:** Recover **preferences over outcomes** from data on which **matchings were chosen**
  - Placement outcomes (duration and disruptions) are **lotteries**

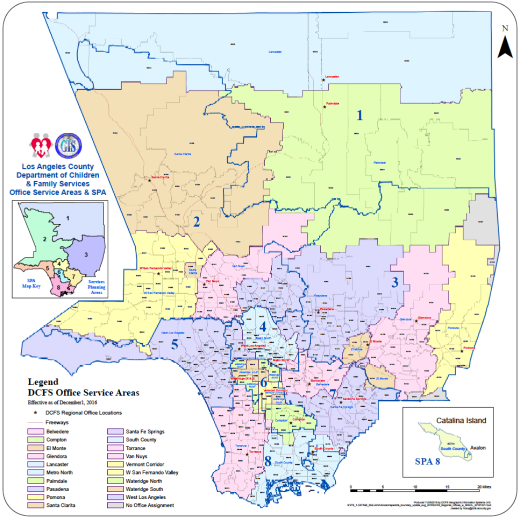
  ⇒ Need to estimate **conditional distribution of outcomes**

- **Problem** Possible selection on **unobservables**
  - Unobservables → Expected match outcomes → Matching → Observed outcomes are selected
  - **Endogeneity** when estimating distribution of outcomes conditional on observables

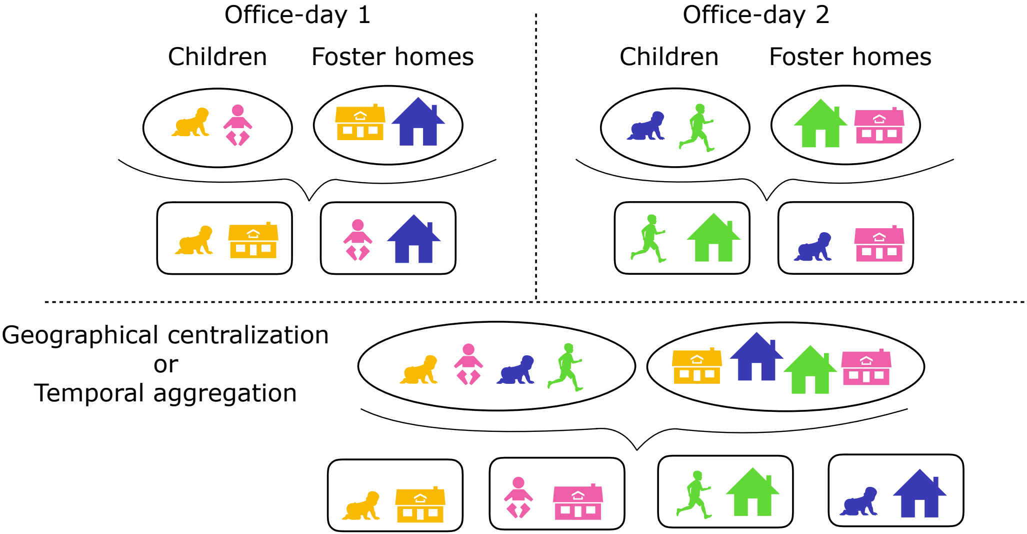
- **Solution**
  - **Structural model** of **matching** and **placement outcomes**, with **unobserved heterogeneity**
  - **Identification** Exogenous variation across dates and regions at which children enter foster care

Los Angeles County, CA

- Foster care administered at the **county level**
- **Data** Confidential administrative records from LA child-protective services agency
- **County with most foster children** in the U.S.
  - On any given day, **17,000** children in foster care
  - **40** children assigned to a foster home everyday
  - **19** regional offices (color-coded)
- **Largest and most populated** county in the U.S.
  - **Population** = 10.16 million (26% of California)
  - **Area** = 4,751 mi^2 (85% of Connecticut)
  - If it were a state, top-10 pop., 3rd smallest



Market Thickness



Office-day 1

Children Foster homes

Office-day 2

Children Foster homes

Geographical centralization
or
Temporal aggregation

Main Findings

- Within regional offices, social workers do a **“good job”** assigning children to foster homes
  - Placements **more likely to be disrupted are less likely to be assigned**
  - Matching choices also reveal **preferences over duration** (beyond disruption)
  - Social workers **minimize disruptions and the time children stay in foster care**

- **Decentralization** into regional offices **is sub-optimal**: if system were centralized...
  - Avg. $\mathbb{P}(\textit{disruption}) \downarrow 4.2$ %-pts $\implies 8\% \downarrow$ placements per child before exiting foster care
  - 54% less distance between foster homes and schools
- ↑ market thickness by **delaying assignments does not improve outcomes substantially**
- **Moral** *Social workers do a good job at matching, but exogenous institutions cause inefficiencies*
- **Policy Conclusion** *Improve coordination between regional offices, do not delay assignments*

Related Literature

Foster Care
and
Adoption

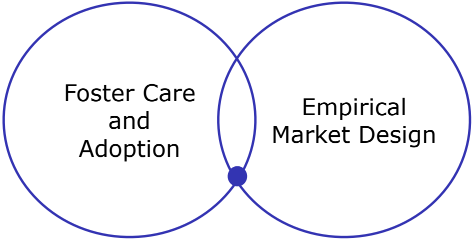
Market and Application

- Matching
  - Baccara, Collard-Wexler, Felli, and Yariv 2014
  - Slaugh, Akan, Kesten, and Ünver 2015
  - MacDonald 2019
- Foster Care Outcomes
  - Doyle Jr. and Peters 2007
  - Doyle Jr. 2007; 2008; 2013
  - Doyle Jr. and Aizer 2018

Contributions:

- Policy analysis (market thickness)
- Co-dependence of matching and outcomes

Related Literature



Foster Care and Adoption

Empirical Market Design

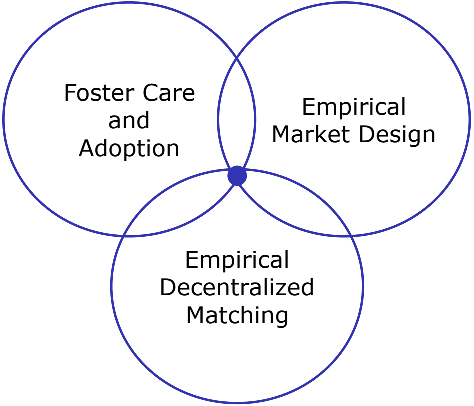
Research Agenda: Empirical study of centralized matching markets

- Medical Match
  - Agarwal 2015
- School Choice
  - Abdulkadiroğlu, Agarwal, and Pathak 2017
  - Agarwal and Somaini 2018
  - Artemov, Che, and He 2019
- Kidney Exchange
  - Agarwal, Ashlagi, Azevedo, Featherstone, and Karaduman 2017
  - Agarwal, Ashlagi, Rees, Somaini, and Waldinger 2019

Contribution:

- New domain of centralized matching (w/o matching algorithm)

Related Literature



Foster Care and Adoption

Empirical Market Design

Empirical Decentralized Matching

Equilibrium Matching Models

- Marriage market
  - Choo and Siow 2006
  - Chiappori, Oreffice, and Quintana-Domeque 2012
  - Galichon and Salanié 2015
  - Fox 2010; 2018
- Dating, Taxi market,...
  - Hitsch, Hortaçsu, and Ariely 2010
  - Fréchette, Lizzeri, and Salz 2019
  - Buchholz 2019

Contributions:

- Matching with disruptions
- Preferences over match-outcomes induce selection

Outline

1. Background and Data
2. Model
3. Identification and Estimation
4. Estimation Results
5. Counterfactual Policy Analysis

Background and Data

- **Data** Confidential county records (accessed through court order) from the Los Angeles County Department of Children and Family Services (DCFS)
- **Dataset** Records of all children who went through foster care between 2006 and 2016 (FY)
  - 112,755 **children** | 129,084 **foster care episodes** | 266,887 **placements**
  - Avg. episodes per child = 1.14
  - Avg. placements per episode = 2.09
  - Avg. episode duration = 14.02 months (median = 10.32 months)
  - Avg. placement duration = 7.39 months (median = 3.67 months)
- **Sample** Every placement assigned between January 1, 2011, and February 28, 2011
  - 2,087 **children** | 2,358 **placements**
  - **Children characteristics** Age, school zip-code
  - **Foster homes characteristics** Type (county, agency, group-home, relative), zip-code

Description of markets and excess supply

- **Market** = **day** × **regional office** × **relatives**
- Foster homes are observed conditional on being matched
  - Excess supply is **not observed, but relatively small**
  - Children are left **unmatched** only if there are **no foster homes available**
- Description of markets
  - **Sample period** = 58 days | **Regional offices** = 19 days | **Office-days** = 1102
  - Office-days with $\geqslant 1$ **child without a relative** = 90.7%
    - At least one **unmatched child** in 88.1% of these office-days
  - 85% children are matched on same day they need a placement
  - Avg. **waiting time** (of those who wait) = 6.5 days
  - **Takeaway** Most children matched right away, but unmatched children in almost all office-days

Summary Statistics

	n	mean	sd	median
Termination Reasons				
Disruption	2358	0.51	0.5	1
Permanency	2358	0.42	0.49	0
Reunification	2358	0.31	0.46	0
Adoption	2358	0.12	0.32	0
Emancipation	2358	0.052	0.2	0
Censored	2358	0.015	0.12	0
Duration				
Duration (months)	2358	8.37	11.28	4.31
Duration—Disrup	1201	5.4	7.96	2.43
Duration—Perm	999	9.97	9.99	7.31
Duration—Emanc	122	12.94	14.3	7.61
Duration—Cens	36	47.89	27.88	64.56
Placement Characteristics				
Child's Age	2358	8.69	5.97	8.49
County Foster Home	2358	0.086	0.27	0
Agency Foster Home	2358	0.43	0.5	0
Group Home	2358	0.12	0.32	0
Relative Home	2358	0.37	0.48	0
Distance Plac-School (mi.)	1775	18.13	23.77	7.99
No School	2358	0.25	0.43	0

Note: Distance measures at zip-code level, computed using Google Maps API.

Summary Statistics (full sample)

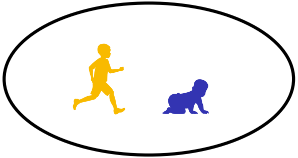
	n	mean	sd	median	mean-full	sd-full
Termination Reasons						
Disruption	2358	0.51	0.5	1	0.49	0.5
Permanency	2358	0.42	0.49	0	0.37	0.48
Reunification	2358	0.31	0.46	0	0.26	0.44
Adoption	2358	0.12	0.32	0	0.11	0.31
Emancipation	2358	0.052	0.2	0	0.048	0.21
Censored	2358	0.015	0.12	0	0.090	0.27
Duration						
Duration (months)	2358	8.37	11.28	4.31	8.12	10.66
Duration—Disrup	1201	5.4	7.96	2.43	4.86	7.38
Duration—Perm	999	9.97	9.99	7.31	10.4	9.90
Duration—Emanc	122	12.94	14.3	7.61	13.23	15.93
Duration—Cens	36	47.89	27.88	64.56	13.99	17.28
Placement Characteristics						
Child's Age	2358	8.69	5.97	8.49	8.55	5.91
County Foster Home	2358	0.086	0.27	0	0.09	0.29
Agency Foster Home	2358	0.43	0.5	0	0.36	0.48
Group Home	2358	0.12	0.32	0	0.11	0.32
Relative Home	2358	0.37	0.48	0	0.43	0.5
Distance Plac-School (mi.)	1775	18.13	23.77	7.99	15.75	23.31
No School	2358	0.25	0.43	0	0.33	0.47

Note: Distance measures at zip-code level, computed using Google Maps API.

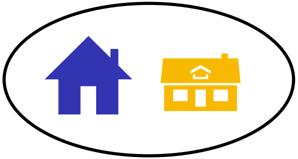
Model

FOSTER CARE — An Assignment Problem

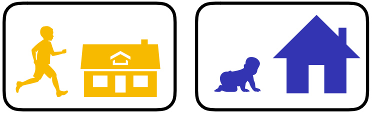
Children in need of care



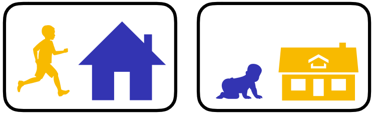
Foster homes



Matching 1



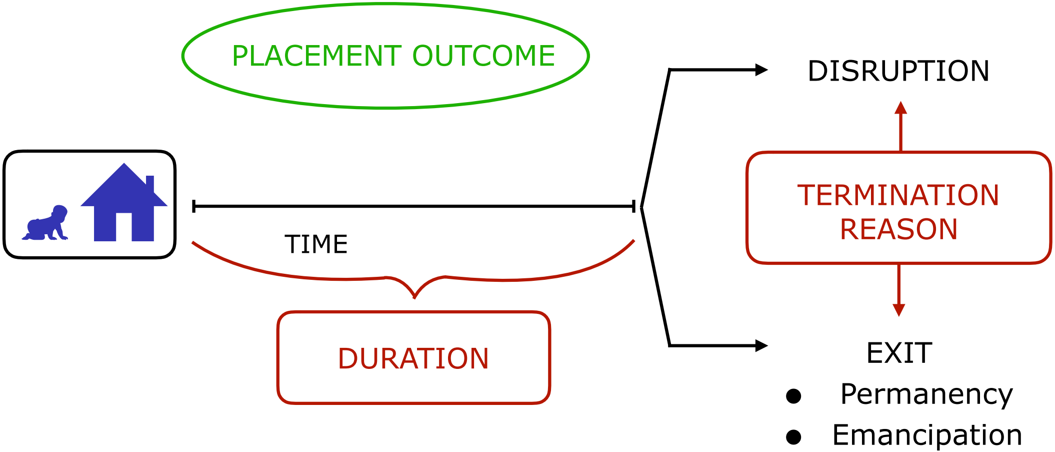
Matching 2



QUESTIONS:

1. How are children assigned to foster homes?
2. What are the implications of an assignment?

IMPLICATIONS of an assignment



PLACEMENT OUTCOME

TIME

DURATION

DISRUPTION

TERMINATION REASON

EXIT

- Permanency
- Emancipation

Model: Notation

- **Market** $(C, H, \mathbf{X}, \mathbf{Y})$
  - C and H sets of available children and foster homes
  - $\mathbf{X} = (\mathbf{x}_c)_{c \in C}$ and $\mathbf{Y} = (\mathbf{y}_h)_{h \in H}$ children's and homes' observable characteristics
  - Market i = day × regional office × relatives
- **Types** Coarsening of observable characteristics
  - $x_c \in X$ and $y_h \in Y$ denote c's and h's types
- **Matching** $M : C \times H \rightarrow \{0, 1\}$

$$M(c, h) = 1\{\text{child } c \text{ is matched with home } h\}$$

Model: Notation

- **Placement outcome** $(T, R) \in \mathbb{R}_+ \times \mathcal{R}$, where
  - T = duration
  - R = termination reason $\in \mathcal{R} \equiv \{$ disruption(d), exit to permanency(ex), emancipation(em) $\}$
- **Data**
  - Exogenous variables: $(C_i, H_i, \mathbf{X}_i, \mathbf{Y}_i)_{i=1}^n$
  - For each market i, the observed endogenous variables
    - $M_i \in \mathbb{M}(C_i, H_i)$ matching chosen
    - $(\mathbf{T}_i, \mathbf{R}_i)_{i=1}^n$ placement outcomes, where $\mathbf{T}_i = (T_{ch})_{(c,h)\in M_i}$, and $\mathbf{R}_i = (R_{ch})_{(c,h)\in M_i}$

Only the outcomes of the placements that are assigned are observable

1. Social Workers' Matching Problem

- Central planner (DCFS) assigns placements
- Utility over realized placement outcomes:

$$u(T, R; T_{em}) = \mu_R + \varphi_R \log T + \bar{\varphi}_R \log T_{em}$$

- Assign placements according to

$$\max \left\{ \sum_{c \in C, h \in H} M(c,h) \; \left[\pi(c,h) + \varepsilon_{c y_h} + \eta_{x_c h}\right] : M \in \mathbb{M}(C,H) \right\},$$

  - $\pi(c,h) = \mathbb{E}\left[u(T, R; T_{em}) \mid \mathcal{I}_{ch}\right]$ "deterministic" component ("systematic preferences")
  - $\mathcal{I}_{ch}$ = central planner's information about (prospective) placement (c,h)
  - ε_{cy} "idiosyncratic" surplus of placing child c in home of type y ("child-taste variation")
  - η_{xh} "idiosyncratic" surplus of placing a child of type x in home h ("home-taste variation")

1. Multinomial Probit Model of Matching

- Econometrician's perspective:

$$M(C,H,\mathbf{X},\mathbf{Y}) = \operatorname{arg\,max}\left\{\sum_{c\in C,h\in H} M(c,h)\pi(c,h) + \upsilon_M : M \in \mathbb{M}(C,H)\right\},$$

where υ_M is the composite random error given by:

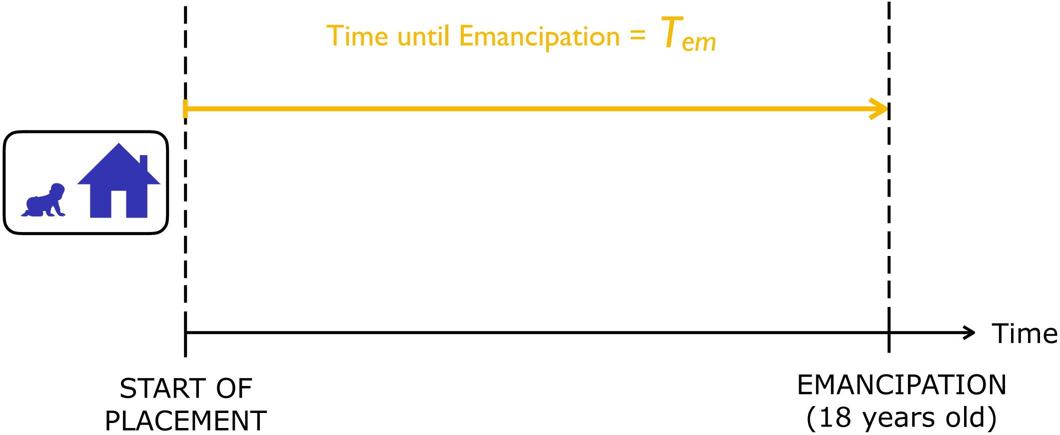
$$\upsilon_M \equiv \sum_{c\in C,h\in H} M(c,h)[\varepsilon_{cy_h} + \eta_{x_c h}]$$

Assumption 1: Composite Matching Error

Let $\varepsilon_c = (\varepsilon_{cy})_{y\in Y}$ and $\eta_h = (\eta_{xh})_{x\in X}$. Assume, for all $c, c' \in C$, and $h, h' \in H$,

$$\varepsilon_c \sim N(0,\mathbf{\Sigma}_\varepsilon), \quad \eta_h \sim N(0,\mathbf{\Sigma}_\eta), \quad \varepsilon_c \perp \varepsilon_{c'}, \quad \eta_h \perp \eta_{h'}, \quad \text{and} \quad \varepsilon_c \perp \eta_h.$$

2. Competing Risks Duration Model of Placement Outcomes



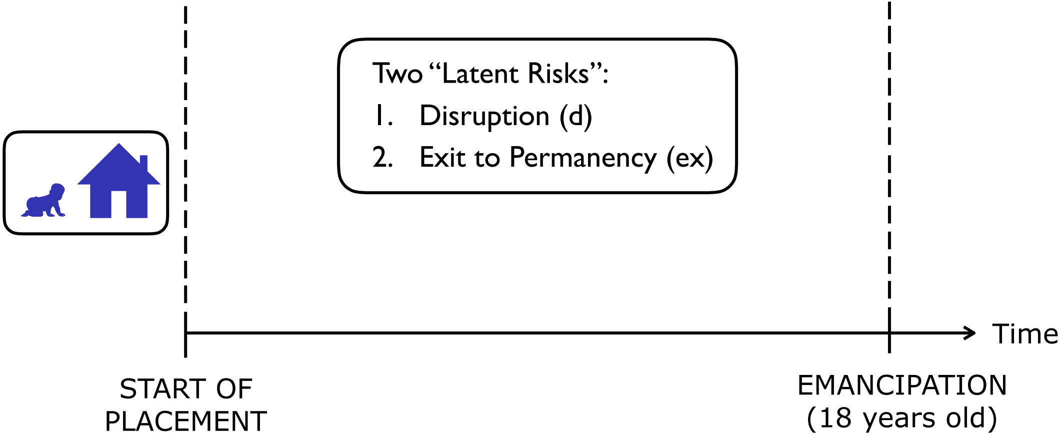
Time until Emancipation = T_{em}

Time

START OF
PLACEMENT

EMANCIPATION
(18 years old)

2. Competing Risks Duration Model of Placement Outcomes



Two "Latent Risks":

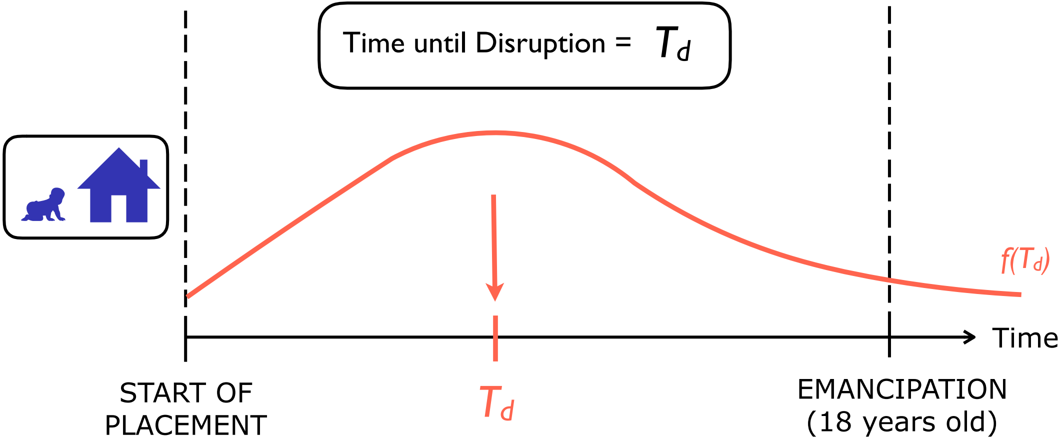
1. Disruption (d)
2. Exit to Permanency (ex)

Time

START OF
PLACEMENT

EMANCIPATION
(18 years old)

2. Competing Risks Duration Model of Placement Outcomes



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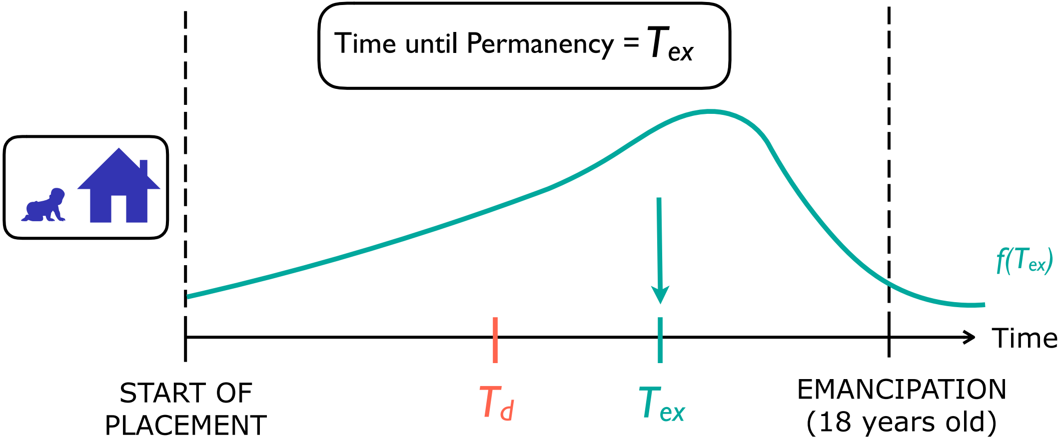

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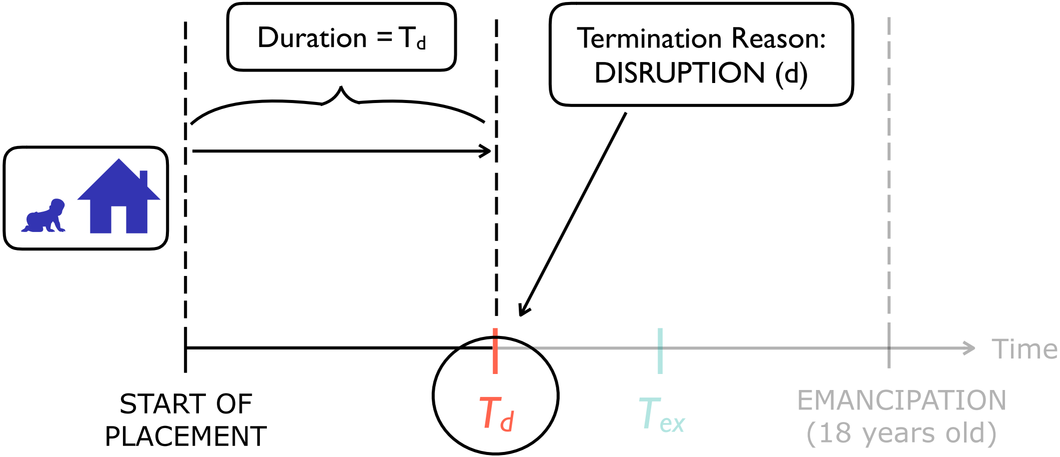

Duration = T_d

Termination Reason:
DISRUPTION (d)

Time

START OF
PLACEMENT

T_d

T_{ex}

EMANCIPATION
(18 years old)

2. Competing Risks Duration Model of Placement Outcomes

- T_R is the latent duration for $R \in \mathcal{R}$, and

$$T = \min\{T_R : R \in \mathcal{R}\} \quad \& \quad R = \arg\min\{T_R : R \in \mathcal{R}\}.$$

- Need to specify the **conditional outcome distribution**: $(T, R) \mid \mathcal{I}_{ch}$
  - $\mathcal{I}_{ch}$ = central planner's information about (prospective) placement (c, h)

2. Competing Risks Duration Model of Placement Outcomes

- T_R is the latent duration for $R \in \mathcal{R}$, and

$$T = \min\left\{T_R : R \in \mathcal{R}\right\} \quad \& \quad R = \arg\min\left\{T_R : R \in \mathcal{R}\right\}.$$

Assumption 2: Normal Mixing Distribution

The **central planner's information** of a placement is $\mathcal{I}_{ch} = (\mathbf{x}_c, \mathbf{y}_h, \boldsymbol{\omega}_{ch})$ where:

$\boldsymbol{\omega}_{ch} = (\omega_d, \omega_{ex})$ are unobservable **frailty terms** (or random effects)

$$\boldsymbol{\omega}_{ch} \sim N(0, \boldsymbol{\Sigma}_\omega)$$

Note: "Frailty term" means that ω_R shifts the hazard rate of T_R

2. Competing Risks Duration Model of Placement Outcomes

- T_R is the latent duration for $R \in \mathcal{R}$, and

$$T = \min\{T_R : R \in \mathcal{R}\} \quad \& \quad R = \arg\min\{T_R : R \in \mathcal{R}\}.$$

Assumption 3: Burr Hazard Rates

3a. For $R \in \{d, ex\}$, conditional on $\mathcal{I}_{ch}$, T_R follows a **Burr distribution** with hazard rate:

$$\lambda_R(T \mid \mathcal{I}_{ch}) = \frac{k_R(\mathcal{I}_{ch})\alpha_R T^{\alpha_R - 1}}{1 + \gamma_R^2 k_R(\mathcal{I}_{ch}) T^{\alpha_R}}$$

where $\alpha_R > 0$, $\gamma_R \geqslant 0$, and $k_R(\mathcal{I}_{ch}) = \exp(\omega_{R,ch} + g(\mathbf{x}_c, \mathbf{y}_h)\beta_R)$. **Note 1:** α_R and γ_R determine the shape (duration-dependence) of the hazard rate $\lambda_R(T \mid \mathcal{I}_{ch})$ **Note 2:** $\lambda_R(T \mid \mathcal{I}_{ch})$ is increasing in $k_R(\mathcal{I}_{ch})$

3b. Latent durations are independent conditional on $\mathcal{I}_{ch}$, $\boldsymbol{\omega}_{ch} \perp \varepsilon_c$, and $\boldsymbol{\omega}_{ch} \perp \eta_h$.

Model Recap

- Utility over realized placement outcomes:

$$u(T, R; T_{em}) = \mu_R + \varphi_R \log T + \bar{\varphi}_R \log T_{em}$$

- Matchmaker assigns placements according to

$$\max \left\{ \sum_{c \in C, h \in H} M(c,h) \left[\pi(c,h) + \varepsilon_{cy_h} + \eta_{x_c h} \right] : M \in \mathbb{M}(C,H) \right\}$$

  - Match surplus: $\pi(c,h) = \mathbb{E}\left[u(T, R; T_{em,c}) \mid \mathbf{x}_c, \mathbf{y}_h, \boldsymbol{\omega}_{ch} \right]$
    - Placement Outcome: $(T,R)|(\mathbf{x}_c, \mathbf{y}_h, \boldsymbol{\omega}_{ch}) \sim$ Burr Competing Risks
    - Unobserved Heterogeneity: $\boldsymbol{\omega}_{ch} \sim$ Normal Mixing Distribution
    - Note: $(T,R)|(\mathbf{x}_c, \mathbf{y}_h) \sim$ Mixed Burr Competing Risks
  - Child-taste variation: $\varepsilon_{cy} \sim N(0, \boldsymbol{\Sigma}_\varepsilon)$
  - Home-taste variation: $\eta_{xh} \sim N(0, \boldsymbol{\Sigma}_\eta)$

Identification and Estimation

Data Generating Process (DGP)

- Need to identify the distribution of the **endogenous** ("left-hand side") variables

  $$(M_i, \mathbf{T}_i, \mathbf{R}_i),$$

  conditional on the **exogenous** ("right-hand side") ones

  $$(C_i, H_i, \mathbf{X}_i, \mathbf{Y}_i).$$

- Also, need to identify distribution of the **unobserved heterogeneity** ("mixing distribution")

  $$(M_i, \mathbf{T}_i, \mathbf{R}_i) \,|\, (C_i, H_i, \mathbf{X}_i, \mathbf{Y}_i) \sim \int (M_i, \mathbf{T}_i, \mathbf{R}_i) \,|\, (C_i, H_i, \mathbf{X}_i, \mathbf{Y}_i, \mathbf{\Omega}_i) dG(\mathbf{\Omega}_i),$$

  where $\mathbf{\Omega}_i = (\boldsymbol{\omega}_{ch})_{(c,h) \in C_i \times H_i}$.

Identification

1. Duration Distribution (hazard rates and unobserved heterogeneity)
   - **Mixed competing risks** with covariates identified **non-parametrically** (Heckman and Honoré 1989).
   - Distribution of $\boldsymbol{\omega}$ across observed outcomes is **conditional on being matched**: $\boldsymbol{\omega}_{ch} \,|\, M(c,h) = 1$.
   - **Exogenous variation** in $(C, Y, \mathbf{X}, \mathbf{Y})$ across markets identifies distribution of $\boldsymbol{\omega}$ (Ackerberg and Botticini 2002; Sørensen 2007).
     - Intuition akin to traditional **sample selection** models (Heckman 1979)

2. Matching Distribution (multinomial probit)
   - **Utility index** $\sum_{c,h} M(c,h)\pi(c,h)$ **linear** in utility parameters $(\mu_R, \varphi_R, \bar{\varphi}_R)_{R \in \mathcal{R}}$.
   - Distribution of **individual shocks** ε_c and η_y can be backed out from **composite error** υ_M
   - Exploit variation in $(C, Y, \mathbf{X}, \mathbf{Y})$ across markets, and observing **unmatched children**.

Estimation

- Estimate via **Simulated Maximum Likelihood**.
- Collect all the parameters of the model:

$$\boldsymbol{\theta}_T = (\boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\beta}); \quad \boldsymbol{\theta}_M = (\boldsymbol{\mu}, \boldsymbol{\varphi}, \bar{\boldsymbol{\varphi}}, \boldsymbol{\Sigma}_\epsilon, \boldsymbol{\Sigma}_\eta); \quad \boldsymbol{\theta} = [\boldsymbol{\Sigma}_\omega, \boldsymbol{\theta}_T, \boldsymbol{\theta}_M].$$

- The likelihood of observing $(M_i, \mathbf{T}_i, \mathbf{R})$, conditional on $\boldsymbol{\Omega}_i = (\boldsymbol{\omega}_{ch})_{(c,h)\in C_i \times H_i}$, is given by:

$$\mathcal{L}(M_i, \mathbf{T}_i, \mathbf{R}_i \,|\, \boldsymbol{\Omega}_i, \boldsymbol{\theta}_T, \boldsymbol{\theta}_M) = \mathcal{L}_M(M_i \,|\, \boldsymbol{\Omega}_i, \boldsymbol{\theta}_T, \boldsymbol{\theta}_M) \prod_{(c,h)\in M_i} \mathcal{L}_{\mathbf{T},\mathbf{R}}(T_{ch}, R_{ch} \,|\, \boldsymbol{\omega}_{ch}, \boldsymbol{\theta}_T),$$

where:

$$\mathcal{L}_M(M_i \,|\, \boldsymbol{\Omega}_i, \boldsymbol{\theta}_T, \boldsymbol{\theta}_M) = \text{probit choice probability}$$

$$\mathcal{L}_{\mathbf{T},\mathbf{R}}(T_{ch}, R_{ch} \,|\, \boldsymbol{\omega}_{ch}, \boldsymbol{\theta}_T) = \text{Burr competing risks conditional likelihood}$$

Estimation

- Let $G = \times_{c,h} G_{ch}$ denote the distribution of $\mathbf{\Omega}_i$, i.e., $G_{ch} \equiv N(0, \mathbf{\Sigma}_\omega)$. Then,

$$\mathcal{L}(M_i, \mathbf{T}_i, \mathbf{R}_i \,|\, \boldsymbol{\theta}) = \int \mathcal{L}_M(M_i \,|\, \mathbf{\Omega}_i, \boldsymbol{\theta}_T, \boldsymbol{\theta}_M) \prod_{(c,h)\in M_i} \mathcal{L}_{\mathbf{T},\mathbf{R}}(T_{ch}, R_{ch} \,|\, \boldsymbol{\omega}_{ch}, \boldsymbol{\theta}_T) dG(\mathbf{\Omega}_i \,|\, \mathbf{\Sigma}_\omega).$$

- The log-likelihood of the data is $\ell(\boldsymbol{\theta}) = \sum_{i=1}^n \log \mathcal{L}(M_i, \mathbf{T}_i, \mathbf{R}_i \,|\, \boldsymbol{\theta})$.
- Simulated analog of $\mathcal{L}$:

$$\mathcal{L}^{S_\upsilon, S_\omega}(M_i, \mathbf{T}_i, \mathbf{R}_i \,|\, \boldsymbol{\theta}) = \frac{1}{S_\upsilon} \frac{1}{S_\omega} \sum_{s_\upsilon=1}^{S_\upsilon} \sum_{s_\omega=1}^{S_\omega} \mathcal{L}_M^{s_\upsilon} \left(M_i \,|\, \mathbf{\Omega}_i^{s_\omega}, \boldsymbol{\theta}\right) \prod_{(c,h)\in M_i} \mathcal{L}_{\mathbf{T},\mathbf{R}} \left(T_{ch}, R_{ch} \,|\, \boldsymbol{\omega}_{ch}^{s_\omega}, \boldsymbol{\theta}_T, \mathbf{\Sigma}_\omega\right),$$

  where $\mathcal{L}_M^{s_\upsilon}$ is the simulated probit choice probability using a logit-kernel (Train 2009).

- The SMLE of $\boldsymbol{\theta}$ is given by: $\hat{\boldsymbol{\theta}}_{SMLE} = \arg\max_{\boldsymbol{\theta}} \sum_{i=1}^n \log \mathcal{L}^{S_\upsilon, S_\omega}(M_i, \mathbf{T}_i, \mathbf{R}_i \,|\, \boldsymbol{\theta})$
- $\hat{\boldsymbol{\theta}}_{SMLE} \overset{a}{=} \hat{\boldsymbol{\theta}}_{MLE}$ (**consistent**, **asymptotically normal** and **efficient**) if $n, S_\upsilon, S_\omega \to \infty$, and $\sqrt{n}/\min(S_\upsilon, S_\omega) \to 0$ (Gourieroux and Monfort 1997).

Estimation Results

Matching Utility

Matching Utility—Parameter Estimates

	Disruption	Permanency	Emancipation
μ_R — *MgU. Term. Reason*	-2.908***	2.449**	-2.057***
	(0.6972)	(1.091)	(0.7183)
φ_R — *MgU. Duration*	-0.355***	-0.527***	0†
	(0.101)	(0.167)	(0)
$\bar{\varphi}_R$ — *MgU. Emanc. Time*	0.3093***	-0.1179	0.009985
	(0.0617)	(0.0961)	(0.0136)
Number of markets (n)		1,467	
SMLL		-17005.86	

Note: $u = \mu_R + \varphi_R \log T + \bar{\varphi}_R \log T_{em}$. Standard errors in parenthesis. Significance level of parameters: ***p$\leqslant$0.01, **p$\leqslant$0.05, *p$\leqslant$0.01. † indicates fixed parameter (not estimated). Estimation via Simulated Maximum Likelihood.

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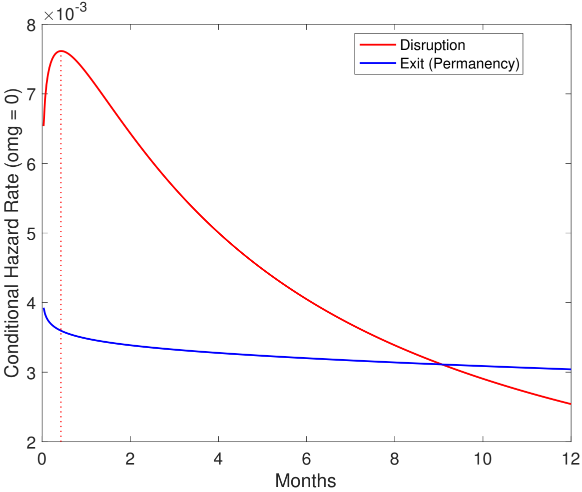
- Placements more likely to be disrupted are less likely to be assigned
- Social workers minimize the time children stay in foster care
- Social workers reveal preferences over children's age conditional on termination reason

Estimated Hazard Rates

Parameter Estimates Model Fit



Average Partial Effects on Expected Outcomes

Average Partial Effects

	$\mathbb{P}$(Disrup)	$\mathbb{P}$(Perman)	$\mathbb{E}(\log T \mid \text{Disrup})$	$\mathbb{E}(\log T \mid \text{Perman})$	$\mathbb{E}(\log T)$
Age At Plac.	0.0139	-0.0115	-0.0406	-0.022	-0.0401
County-FH	0.317	-0.266	-0.969	-0.628	-0.927
Agency-FH	0.320	-0.272	-1.221	-0.874	-1.174
Group Home	0.165	-0.158	0.287	0.450	0.339
Distance To School (zip)	0.00401	-0.00376	-0.007978	-0.00309	-0.00736
No School	0.1136	-0.09686	-0.5244	-0.3653	-0.5212
Number of placements			2358		

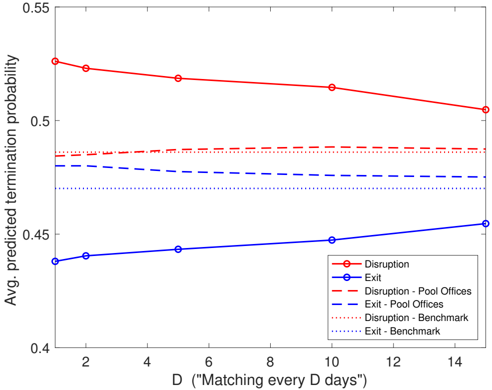
Note: Average partial effects of placement characteristics on expected outcomes. Averages taken across the sample of assigned placements in the data. The partial effects with respect to continuous variables is taken by considering a marginal change of one unit.

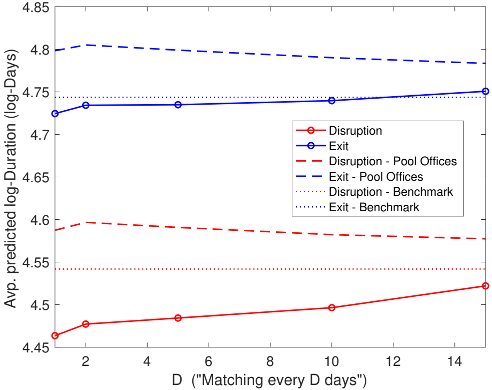
Counterfactual Policy Analysis

Counterfactual Policy Analysis

- Increasing market thickness by aggregating markets
  - **Centralization** Pool regional offices together into a single county-wide market
  - **Temporal aggregation** Assign placements within regional offices every $D \geqslant 1$ days
  - **Benchmark** Pool regional offices together and match everyone at once ($D = \infty$)
- Assume zero costs of information aggregation
  - Obtain upper bound of gains from greater market thickness

Spatial and Temporal Aggregation: Expected Outcomes

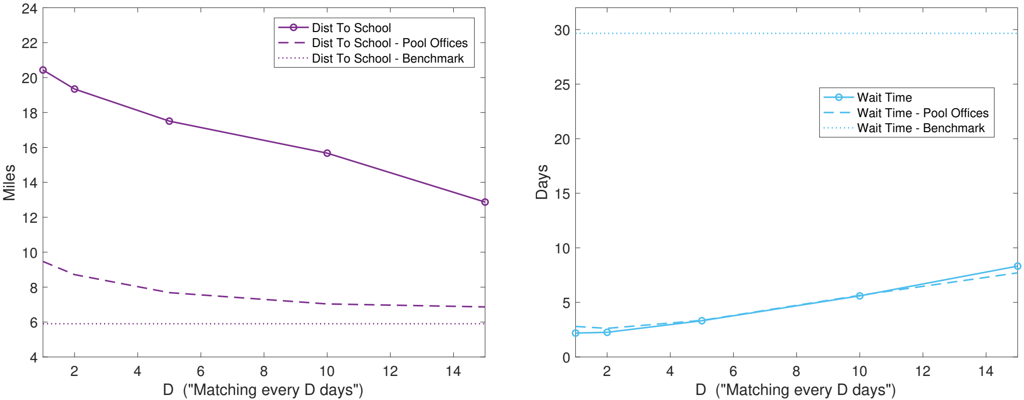




Notes:

- y-axis = avg. termination probability (left), avg. conditional log-duration (right)
- x-axis = temporal aggregation
- dashed lines = spatial aggregation
- dotted lines = maximum market thickness

Spatial and Temporal Aggregation: School Distance and Waiting Time



Notes:

- y-axis = avg. distance to school (left), avg. waiting time (right)
- x-axis = temporal aggregation
- dashed lines = spatial aggregation
- dotted lines = maximum market thickness

Conclusion

- **Objective** Formulate and estimate **structural model** of placement assignment and outcomes
- **Who gets placed where and why?**
  - Social workers do a **"good job"** assigning children to foster homes within regional offices
- **However,...**
  - Regional offices **coordinate sub-optimally** with one another.
  - There are **gains from centralizing the assignment of placements** across LA County
    - $\mathbb{P}(disruption) \downarrow$ 4.2 %-pts $\Longrightarrow$ 8% $\downarrow$ fewer foster homes per child
    - 54% less distance between foster homes and schools
- **What do we learn?**
  - Social workers do a **good job** at matching, but **exogenous institutions cause inefficiencies**
  - **Policy recommendation** Improve coordination between regional offices, do not delay assignments

Conditional Hazard Functions Back

	Disruption	Exit
Var(ω_R)	0.873***	0.02955
	(0.2912)	(0.02867)
Cov(ω_d, ω_{ex})	0.1573*	0.1573*
	(0.08908)	(0.08908)
Age At Plac.	0.09872***	-0.01615
	(0.01767)	(0.01047)
County-FH	2.217***	-0.02375
	(0.332)	(0.2101)
Agency-FH	2.983***	0.4547***
	(0.2556)	(0.1237)
Group Home	-2.077**	-1.987***
	(0.9188)	(0.5642)
Age At Plac. × *County-FH*	-0.02272	0.01804
	(0.0261)	(0.01636)
Age At Plac. × *Agency-FH*	-0.07878***	-0.01007
	(0.0194)	(0.0124)
Age At Plac. × *Group Home*	0.2569***	0.1419***
	(0.06179)	(0.03894)
Distance To School (zip)	0.02052***	-0.006059***
	(0.002471)	(0.001724)
No School	0.9007***	0.1222
	(0.1603)	(0.08942)
Constant	-8.996***	-6.082***
	(0.5408)	(0.2132)
Alpha (α_R)	1.091***	0.9665***
	(0.07551)	(0.03427)
Gamma (γ_R)	0.9527***	0.2222
	(0.1183)	(0.2361)
Number of placements	2358	

Note: Estimated parameters of unobserved heterogeneity ($\boldsymbol{\Sigma}_\omega$) and conditional hazard rates ($\boldsymbol{\theta}_T$). Standard errors in parenthesis. Significance level of parameters: ***$p \leqslant 0.01$, **$p \leqslant 0.05$, *$p \leqslant 0.01$.

Model Fit

Back

Goodness of Fit and Estimation Parameters

	Predicted	Sample
$\mathbb{P}(\textit{Disruption})$	0.514	0.5093
$\mathbb{P}(\textit{Permanency})$	0.4303	0.4237
$\mathbb{P}(\textit{Emanc/Cens})$	0.05568	0.06701
$\mathbb{E}(\log T \mid \textit{Disruption})$	4.482	4.141
$\mathbb{E}(\log T \mid \textit{Permanency})$	4.721	4.994
$\mathbb{E}(\log T \mid \textit{Emanc/Cens})$	7.19	5.534
$\mathbb{E}(\log T)$	4.615	4.596
Number of markets (n)	1467	
Number of assigned placements	2358	
Number of prospective placements	8900	
SMLL	-17005.86	
S_ω	50	
S_υ	50	
$\dim(\boldsymbol{\theta})$	39	

Note: Average predicted outcomes and sample average outcomes. Averages taken across the sample of assigned placements in the data. The number of assigned placements in the data is equal to $\sum_i \sum_{c,h} M_i(c,h)$. The number of prospective placements is equal to $\sum_i \sum_{c,h} |C_i| \times |H_i|$. *SMLL* gives the value of the simulated log-likelihood at the estimated vector of parameters. S_ω, S_υ, and ψ are the parameters of the simulated log-lilkelihood. $\dim(\boldsymbol{\theta})$ refers to the number of parameters estimated.